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Hendrikx, A.L.P.M.; Heuts, R.M.J.; Hoving, L.G.

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TILBURG UNIVERSITY
KATHOLIEKE UNIVERSITEIT BRABANT
POSTBOX 90153
5000 LE TILBURG
THE NETHERLANDS

[redacted]

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COMPARISON OF AUTOMATIC MONITORING SYSTEMS IN AUTOMATIC FORECASTING

A.L.P.M. Hendrikx*, R.M.J. Heuts**
L.G. Hoving*

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Hendrikx, A.L.P.M.*
Nederlandse Philips Bedrijven B.V.
Centre for Quantitative Methods
Building HCM-705
P.O. Box 218
5600 MD Eindhoven - The Netherlands
Tel.: 040-758721/040-758625

Heuts, R.M.J.**
Tilburg University
Econometric Department
Buidling B-422
P.O. Box 90153
5000 LE Tilburg - The Netherlands
Tel.: 013-662352

Hoving, L.G.*
Nederlandse Philips Bedrijven B.V.
Centre for Quantitative Methods
Building HCM-823
P.O. Box 218
5600 MD Eindhoven - The Netherlands
Tel.: 040-57776/040-58625

COMPARISON OF AUTOMATIC MONITORING SYSTEMS IN AUTOMATIC FORECASTING

Abstract

This paper compares the performance of several monitoring methods in terms of their ability to detect particular process disturbance types.
The forecast errors are either normally and independently distributed, or are the autocorrelated errors that result from the application of the Holt-Winters extrapolation method to disturbed trendwise time series, or from the application of single exponential smoothing to disturbed time series randomly fluctuating around a constant level. In contrast to other research in this field, aside from the step change, also changes in trend and variance are considered. The main conclusion states the cusum method as the best choice in almost all simulated situations. As such the cusum method is recommended as its superiority more than compensates for the extra effort involved.

Keywords: Monitoring forecast errors, Forecast error type, Process disturbance type, Simulation, Cusum, Holt-Winters extrapolation.

1. Introduction

A shortcoming of automatic extrapolation methods is that they are not able to catch all the changes that occur in a dynamic environment. This, as well as misspecifications in the extrapolation model, can result in bad forecasts. These environmental changes have to be identified as soon as possible in order to refit or replace the forecasting method. Hence, it is desirable to monitor forecast errors when automatic forecasting and extrapolation methods are used. Several monitoring methods have been developed to provide warning signals automatically, when forecasts diverge too much from reality.

In the field of monitoring forecasts, previous research is limited to normally and independently distributed forecast errors and errors of the single exponential smoothing forecasting method. The disturbance was typically identified as a stepwise disturbance (Ref. e.g. Gardner (1983), Golder and Settle (1976)).

This paper tries to complement earlier research in two ways.
Firstly, a new type of forecast error is introduced. Time series often exhibit an increasing or decreasing trend, behind which single exponential smoothing forecasts will lag. Hence, in practice often other extrapolation methods are used. In this research, Holt-Winters' extrapolation method (Winters, 1960) is used to cope with the trendwise behaviour of time series. Hence, errors of the Holt-Winters' forecasting method are introduced.
Secondly, two new process disturbance types are introduced. In practice, more disturbance types than just the stepwise one are imaginable. The process disturbance types included in this research are a step, changes in trend and changes in variance.

Simulation will be used to compare the performance of several monitoring methods. Section 2 presents the examined monitoring methods. Equations are given in appendix A. In section 3 the simulation design and research methodology in terms of performance criterion selected, parameter settings etc. are explained. Subsequently, the results will be presented and the practical implications highlighted.

2. Monitoring methods

The performance of the following monitoring methods has been examined:

- Shewhart's method
- Brown's method
- Trigg's method
- Cusum method
- Shewhart-cusum combination
- Gardner's method

All methods give a signal when the relevant tracking signal exceeds a control limit. When a signal occurs, the process is assumed to be out of control. The above mentioned monitoring methods are briefly outlined below. Relevant equations and starting up procedures are listed in appendix A.

2.1 A brief description of the monitoring methods used

Shewhart's method

The method of Shewhart (1931) monitors individual forcast errors. A signal is given when a forecast error exceeds a prespecified control limit.

Brown's method

The method of Brown (1959) is based on the cumulative sum of the forecast errors. A signal is given when the "standardized" sum of forecast errors exceeds a prespecified control limit.
This method has some disadvantages. Firstly, some very good successive forecasts also might cause a signal. The numerator will remain almost equal, while the denominator decreases quickly because of the applied smoothing. Secondly, the sum of the forecast errors never forgets great process disturbances. Although forecasts are satisfying now, a signal might be caused by a disturbance that occurred long ago.

Trigg's method

The "smoothing error tracking signal" was proposed by Trigg (1964). This method is a modification of Brown's method and tries to overcome its main draw backs.

Cusum method

The graphical aspects of a more sophisticated cusum (cumulative sum) method are discussed by Barnard (1959). Harrison and Davies (1963) discovered a way of efficient numerical implementation of this method. Van Winkel and Fraser (1970) present a variant which not only involves simple computations, but is also easy to understand and interpret. This version keeps track of all historical cumulative sums of forecast errors. In this research the version of Van Winkel and Fraser will be identified as the "cusum method".

Shewhart-cusum combination

Another method that combines the cusum method and Shewhart's method by implementing these in a parallel way (see e.g. Lucas (1982)).

Gardner's method

The method proposed by Gardner (1983) uses an autocorrelation tracking signal. The basic idea is that biased forecast errors tend to have the same sign, so a significant positive autocorrelation between these errors indicates that the forecasting proces is out of control. Gardner does not recommend his method when forecast errors are correlated.

3. The simulation design

To make results interpretable and allow the research to be replicated, the simulation design is briefly clarified next. The following issues will be adressed:

- the time series, the forecasting methods and the type of forecast errors used;
- the process disturbances;
- the performance criterion;
- how an equal performance base was reached for all monitoring methods;
- the performance comparison method;
- the general simulation approach;

3.1 Time series, forecasting methods and forecast error types

This research distinguishes three types of forecast errors:

a) Normally and independently distributed forecast errors (denoted by NID).

b) Single exponential smoothing forecast errors

Another type of forecast error is based on the single exponential smoothing method, also called the SES forecast error. These errors are generated by applying single exponential smoothing to a time series that randomly (NID white noise) fluctuates around a constant level (zero), where the smoothing parameter is determined (minimalisation of the sum of squared errors) by a grid search. The first observation is used as the first level estimate. The resulting SES forecast errors will be autocorrelated.

c) Holt-Winters' forecast errors

A new type of forecast error will be introduced, based on the Holt-winters' extrapolation method and to be identified as HW forecast errors. They are generated by applying Holt-Winters' linear model to a time series that randomly (NID white noise) fluctuates around a trendwise increasing line ($series_t = x_t = t + noise_t$). The Holt-Winters' parameters were determined (minimalisation of the sum of squared errors) by a grid search over the feasible area, defined by McClain and Thomas (1973). As first level and trend estimates, x_2 and (x_2-x_1) were used, where x_1 and $x_2$stand for the first and second observation respectively. The resulting HW forecast errors will be autocorrelated.

3.2 Disturbances

Disturbance types

The disturbance types to be considered are:

- step disturbance:
  a step change in the time series (when single exponential smoothing or Holt-Winters' extrapolation method are applied) or in the NID forecast errors.
- trendwise disturbance (ramp):
  a change in trend in the time series (when single exponential smoothing or Holt-Winters' extrapolation method are applied) or in the NID forecast errors.
- variance disturbance:
  a change in the variance of the time series (when single exponential smoothing or Holt-Winters' extrapolation method are applied) or in the NID forecast errors.

The occurrance of a disturbance

Using NID forecast errors, the disturbances are introduced directly in the forecast errors. With SES and HW forecast errors, the disturbances are introduced in the underlying time series. The effect of the disturbances on the forecast errors will differ with regard to the disturbances introduced, due to the adaptive nature of both extrapolation methods.

The size of a disturbance

The size of a disturbance is related to the variance of the NID forecast errors, or to the variance of the white noise of the time series (for SES and HW forecasting errors).

The step disturbance is $\theta\sigma_e$, where $\theta = 0, 0.5, 1, \ldots, 3$ and σ_e is the standard deviation of NID forecast errors, or the standard deviation of the white noise of the time series (for SES and HW forecast errors). It is added to the time series or the NID forecast errors.

The trendwise disturbance can be obtained by introducing a step disturbance every period.

The variance disturbance is introduced by multiplying either the NID forecast errors or the white noise part of the time series (SES and HW) by a factor $(1+\theta)$, where $\theta = 0, 0.5, 1, \ldots, 3$.

3.3 Performance criteria

Average Run length (ARL)

The performance criterion used most is the ARL. Unfortunately, in industrial control as well as in a forecasting context, there exist several different definitions of ARL. Two important definitions are:

Definition 1:
ARL is the average number of periods that elapses before a signal succeeds another.

Definition 2:
ARL is the average number of periods required to detect a disturbance in the monitored process (from the moment the disturbance occurred).

Using both definitions, a good monitoring method has a high ARL when a process is in control and vice versa. Alternate definitions do exist.

Alternative performance criteria

Many other performance criteria are imaginable, but they do not abound in the literature. Some alternatives are:

- the runlength distribution
- quantiles of the runlength distribution
- confidence intervals based on the runlength distribution
- cumulative distribution of the tracking signal
- probability that a tracking signal exceeds a (user specified) control limit. See e.g. Trigg (1964) and Gardner (1983)
- cost/benefit analysis of fast signaling vs. amount of false alarms (signals given erroneously). See e.g. Taylor (1968) and Chiu (1973, 1974).

The choice of the performance criterion

In this research the commonly accepted ARL will be used as performance measure.
The purpose of monitoring methods is to detect "out of control" situations of a process. Principally, one wants to use a method which detects an arbitrary disturbance the fastest. Hence, ARL definition 2 will be used throughout this paper.

3.4 Equal performance base

All monitoring methods should operate under similar conditions, otherwise no comparison of their performance can be made unambiguously. In the simulation research this was established as follows.

Run-in interval

All monitoring methods were granted an interval of 20 periods to eliminate effects of specific starting up conditions. This interval is known as the run-in interval. Process disturbances were introduced in period 21.

False alarm rate

A signal that is given when the process is in control, is known as a false alarm. The false alarm interval is measured in the same way as the response time to a disturbance. All monitoring methods have a false alarm rate of 0.01 (on average one signal per 100 periods). This means that, though the process is in control, all methods give an out of control signal once every hundred periods. Hence, for all methods ARL = 100 for a zero disturbance. To accomplish an equal false alarm rate, monitoring parameters and control limits were set by trial and error. The resulting parameters and control limits are tabulated in appendix B.

Common forecast errors

All monitoring methods operated on the same forecast errors. This was established through the use of a variance-reduction technique named "common random numbers". See e.g. Law and Kelton (1982) and Bratley, Fox and Schrage (1983).

3.5 Performance comparison method

The relative performance of the monitoring methods was compared pairwise. Equality of ARL between two methods was tested, where both methods operated on the same forecast error type, the same disturbance type and the same disturbance size. As the standard deviations of the ARL are unknown, the usual t-test is not applicable. Moreover, standard deviations may not be assumed equal for different monitoring methods. Duncan (1965, p. 505) recommends the Aspin-Welch test (Aspin,1949) for situations where estimates of the standard deviations are merely available. A confidence level of 0.99 was used.

3.6 General simulation approach

First, the forecast errors were calculated. Then, an equal false alarm rate was established for all monitoring methods. Next, the size of the selected process disturbance type was introduced immediately after the run-in interval. Its effects on the forecast errors were calculated,after which the run length for all monitoring methods was calculated. This routine was replicated 100 times out of which the ARL's for all methods, all types of forecast errors and all types and sizes of disturbances, were computed. Finally, the performance comparison was made.

4. Simulation results

First method-specific results for all monitoring methods will be discussed. Subsequently, results per disturbance type will be presented, followed by a sensitivity analysis.

4.1 Results per monitoring method

Shewhart's method

Shewhart's method performs much better than one would expect from previous research findings. Until now the main focus has been on stepwise process disturbances. This is precisely the case in which Shewhart's method performs poorly. For all other disturbance types it compares well with the cusum method.

Brown's method

Brown's method performs best when a small parameter (0.1) is chosen.
The method shows an unusual asymptotic behaviour when process disturbances increase, For increasing disturbances, the ARL generally decreases to one period. For Brown's method this is not necessarily true. For some parameter and control limit settings, ARL does not decrease to one for increasing disturbances. An example can be seen in figure 1 (NID forecast errors with a step disturbance). Further details are provided in appendix C.
For HW forecast errors, Brown's method had to be excluded from the research as a false alarm rate of 0.01 signals per period would have led to an excessive use of CPU-time. An extremely high percentage of signals was produced during the run-in interval, although the false alarm rate was still far below 0.01. Making control limits more restrictive to increase false alarm rate, would have led to an even higher percentage of signals during the run-in phase. Obtaining enough observations to compute ARL reliably would have taken too many computer runs.
All monitoring methods tested had a considerably higher percentage of signals during the run-in interval for HW forecast errors in comparison to other types. In particalur Brown's and Trigg's method showed this result. Appendix D clarifies this phenomenon, which is inherent to HW forecast errors.

Trigg's method

Trigg's method performs best when a small parameter (0.1) is chosen. This conclusion supports Gardner (1983).
For HW forecast errors, Trigg's method had to be excluded from the research similarly to Brown's method.

Cusum method

The cusum method appears to be the generally superior automatic monitoring method tested.

Shewhart-cusum combination

Parallel implementation of cusum and Shewhart's method does not yield significantly better results than the cusum method. Although it is obvious, that the parallel implementation will never perform worse than cusum, it is questionable if this methodology is worth the extra effort it takes.

Gardner's method

Gardner (1983) states that his method does not perform better when monitoring parameter values higher than 0.1 are used. In fact higher values than 0.1 cause Gardner's method to perform poorly.
Gardner (1983) does not recommend his monitoring method for autocorrelated forecast errors. Hence, this method was not tested for SES and HW forecast errors.

4.2 Results per disturbance type

Step disturbance

Trigg's method is the fastest detection method when the step disturbance is small. In the other cases cusum shoes the best results. This holds for all forecast error types. This is illustrated in figure 1.
It is worth mentioning that when single exponential smoothing is used, Trigg's ARL equals at least about 20 periods for disturbances upto 0.5 σ_e. After 20 periods only a few percent of the initial disturbance remains in the forecast errors because of the smoothing nature of the extrapolation method. Nevertheless, it would cost a lot of effort to analyse the nature of the signal, though adjustments in the forecasting procedure (and thus monitoring signals) are probably not desired anymore at this point. Hence, the practical relevance of Trigg's better performance seems to be questionable.
For a step disturbance, Shewhart's method generally performs poorly as compared to the other methods tested, except for NID forecast errors with great step disturbances where it outperforms Brown's, Trigg's and Gardner's method (see figure 1).

Trend disturbance

Inherently, all monitoring methods detect a trend disturbance much faster than a step. Even small disturbances of this type are detected quickly. The cusum method performs best for all forecast error types. For SES and HW forecast errors Shewhart's method does not yield significantly different results as compared to results from the cusum method.

Variance disturbance

A variance decrease in the random noise of the time series will result in better forecasts. Hence, absolute SES and HW forecast errors will also decrease. A variance reduction also decreases absolute NID forecast errors. As could be expected a variance decrease was not perceived by any of the tested methods.
For all forecast error types with a variance increase cusum and Shewhart's method once more perform best. There are no statistically significant differences in their performance.
Gardner (1983) states that the ARL of Brown's and Trigg's method is independent of the time series' variance. For Brown this is not entirely true. Some signals are caused by several successive small forecast errors. When the variance increases, these signals will be delayed, so ARL will increase. This will continue until no more signals are triggered by successive small forecast errors. From this point on, the ARL will behave independently of further variance increases.

4.3 Sensitivity analysis

To verify and validate the simulation results, a sensitivity analysis was performed. The most important results can be summarized as:
Increasing the run-in phase from 20 to 60 periods did not affect the ARL curves significantly. Apparently, the initial run-in interval of 20 periods was sufficient to eliminate the effect of starting conditions for the monitoring methods.
Increasing the number of replications from 100 to 1000 in computing the ARL yielded no significantly different results.
The false alarm rate appeared to be very sensitive to changes in the monitoring parameters and control limits. However, for non-zero disturbances, ARL's were not at all sensitive to such changes. Either parameter

of the cusum method could vary by approximately 0.1, without significantly affecting the performance. The control limit of Shewhart's method could vary even 0.2, without significantly affecting the performance.

5. Conclusions

Nearly all cases showed the cusum method to outperform the other methods tested. Its superiority was maintained for all forecast error types and nearly all disturbances. Therefore, figure 4 and 5 are presented.
When single exponential smoothing was applied, Trigg's method performed significantly better than cusum for small step disturbances. This confirms earlier research by Golder and Settle (1976). However, because the ARL equals at least about 20 periods in this case, Trigg's better performance might be rather irrelevant for practical applications.
Gardner (1983) concluded that cusum does not appear to be worth the extra effort. It is obvious that, when not only stepwise process disturbances are considered, cusum is definitely worth considering.
Shewhart's method performs much better as one would conclude from previously reported research. Only step disturbances have been examined till now. This is exactly the one case in which Shewhart's method performs poorly. In all other cases it competes with the cusum method.
The Shewhart-cusum combination does not perform significantly better than cusum alone and hence is not recommended as a viable alternative.

In summary, the cusum method was shown to be the recommended monitoring method, despite the extra effort involved in its implementation. Moreover, cusum seems to be particularly appropriate for process disturbance types other than the stepwise disturbance.

Appendix A: Equations of monitoring methods

In this appendix the equations of all tested monitoring methods are given. The forecast error in period t is denoted by e_t. The sum of forecast errors, in period t, is given as S_t.

Shewhart's method

A signal is given when $|e_t| \geq k.\sigma\hat{}_e$, where $k>0$,

$\sigma\hat{}_e = \{\Sigma_t{}^n{}_{=1}(e_t - e\sim)/(n-1)\}^{1/2}$

and $e\sim = \Sigma_t{}^n{}_{=1} e_t/n$.

Brown's method

$S_t = e_t + S_{t-1}$.

$MAD_t = \alpha|e_t| + (1-\alpha)MAD_{t-1}$, $0<\alpha<1$.

$T_t = S_t/MAD_t$.

$\sigma\hat{}_e = \{\Sigma_t{}^n{}_{=1}(e_t - e\sim)/(n-1)\}^{1/2}$ (similarly to Shewhart's method).

MAD_t is an estimate, in period t, of the mean absolute deviation of the forecast errors.

A signal is given when $|T_t| \geq CL$, where CL is a constant control limit.

In the simulation research, values of $S_0=0$ and $MAD_0=0.8\sigma\hat{}_e$, were used.

Trigg's method

$S_t = \alpha e_t + (1-\alpha)S_{t-1}$, $0<\alpha<1$.

$MAD_t = \alpha|e_t| + (1-\alpha)MAD_{t-1}$.

$T_t = S_t/MAD_t$.

As in Brown's method, MAD_t is defined as the estimate of the mean absolute deviation of the forecast errors in period t.

A signal is given when $|T_t| \geq CL$, where CL is a constant control limit.

In the simulation research, S_t and MAD_t are initialized as in Brown's method.

Although a slightly better performance can be reached by using

$MAD_t = \beta|e_t| + (1-\beta)MAD_{t-1}$ with $\beta<\alpha$, we have chosen for the original method in our simulation.

Cusum method

The cusum method consists of two tests:

1) $S_t^+ = \max\{S_{t-1}^+ + (e_t/\hat{\sigma}_e - k), 0\}$, with $S_0^+=0$, k constant and $\hat{\sigma}_e$ defined as in Shewhart's method.
   A signal is given when $S_t^+ \geq h$, where h is a constant.
2) $S^{-t} = \min\{S^{-t-1} + (e_t/\hat{\sigma}_e + k), 0\}$, with $S^{-0}=0$.
   A signal is given when $S^{-t} \leq -h$.

Shewhart-cusum combination

The equations given for Shewhart's and the cusum method are used in a parallel way.

Gardner's method

$COV_t = \alpha e_t e_{t-1} + (1-\alpha)COV_{t-1}$, $0<\alpha<1$.
$MSE_t = \alpha e_t^2 + (1-\alpha)MSE_{t-1}$.
$R_t = COV_t/MSE_t$.

COV_t and MSE_t are estimates, in period t, of the covariance and mean squared error of the forecast errors, respectively.
A signal is given when $|R_t| \geq CL$, where CL is a constant control limit.

Appendix B: Monitoring parameters and control limits

Monitoring parameters and control limits for all methods are tabulated in table 1. The parameters are defined in appendix A.

forecast errors	monitoring methods	parameter values and control limits
NID	Shewhart Brown Trigg cusum Shewhart-cusum combination Gardner	$k = 2.65$ $(\alpha,CL) = (0.1,15)$ $(\alpha,CL) = (0.1,0.6)$ $(h,k) = (1.0,2.0)$ $(k,(h,k)) = (2.65,(1.0,2.0))$ $(\alpha,CL) = (0.1,0.5)$
SES	Shewhart Brown Trigg cusum Shewhart-cusum combination	$k = 2.54$ $(\alpha,CL) = (0.1,9)$ $(\alpha,CL) = (0.1,0.47)$ $(h,k) = (1.0,1.8)$ $(k,(h,k)) = (2.54,(1.0,1.8))$
HW	Shewhart cusum Shewhart-cusum combination	$k = 2.64$ $(h,k) = (1.0,1.78)$ $(k,(h,k)) = (2.64,(1.0,1.78))$

Table 1. Parameter and control limit settings.

Appendix C: Asymptotic behaviour of Brown's monitoring method when disturbances increase

Detecting any kind of disturbance will take at least one period (see ARL definition 2). Generally ARL will decrease to one period, when disturbances increase. However, for Brown's method this is not always true. For some parameter and control limit settings, Brown's method will not be able to detect some disturbance types in one period, irrespective of the magnitude of the disturbance. This will be illustrated for a step disturbance in NID forecast errors. For impulse and trendwise disturbances, a similar logic pertains.

Let S_t, S_0, MAD_t, MAD_0, T_t, α and CL be defined as in Brown's method (appendix A).

Furthermore define:

e_t = realisation of a NID forecast error at period t, t = 1,2,....

θ = a disturbance, $\theta \geq 0$.

$\theta_1 = \max\{|e_t|,\ t = 1,2,\ldots\}$.

$e'_t = e_t + \theta$. (1)

$S'_t = \Sigma^t_{i=1} e'_i,\ S'_0=0$. (2)

$MAD'_t = \alpha|e'_t| + (1-\alpha)MAD'_{t-1},\ 0<\alpha<1$ and $MAD'_0=0.8\sigma\hat{}_e$. (3)

$T'_t = S'_t/MAD'_t$. (4)

$e^*_t = e_t + \theta_1,\ t = 1,2,\ldots$ (5)

$S^*_t = \Sigma^t_{i=1} e^*_i,\ S^*_0=0$. (6)

$MAD^*_t = \alpha|e^*_t| + (1-\alpha)MAD^*_{t-1},\ 0<\alpha<1$ and $MAD^*_0=0.8\sigma\hat{}_e$. (7)

For large disturbances set $\theta = \theta_1 + \theta_2$, where $\theta_2>0$.

Then (1), (2), (5) and (6) yield:

$S'_t = S^*_t + t\theta_2$. (8)

By induction of (3) we obtain:

$MAD'_t = MAD^*_t + \theta_2(1-(1-\alpha)^t)$. (9)

Substitution of (8) and (9) in (4) yields:

$T'_t = (S^*_t + t\theta_2)/(MAD^*_t + \theta_2(1-(1-\alpha)^t))$.

Hence, $\lim T'_t = t/(1-(1-\alpha)^t)$ for $\theta \to \infty$ (so $\theta_2 \to \infty$).

A signal is given when $T'_t \geq CL$. Hence, for large disturbances a signal is given when $t \geq CL(1-(1-\alpha)^t)$. It is obvious that pairs (α, CL) exist, for which: $M \equiv \min\{t\geq 1,\ t \geq CL(1-(1-\alpha)^t)\} > 1$.

E.g. for Brown's method, applied to NID forcast errors, $(\alpha, CL) = (0.1, 15)$ is such a pair. Lim ARL(Brown) = M = 10 > 1 for $\theta \to \infty$. Hence, for (α, CL) =

(0.1,15), Brown's method never detects a stepwise disturbance (no matter how large) within 10 periods.

The same reasoning does not necessarily pertain to SES and HW forecast errors (equation (4) will be different). However, the simulation results strongly indicate that the above mentioned phenomenon also exists for these types of forecast error.

Appendix D: Percentage of signals during run-in interval for Holt-Winters' forecast errors for Trigg's monitoring method

For all forecast error types a false alarm rate of 0.01 signals per period was obtained. However, HW forecast errors, as compared to other forecast error types, yielded a considerably higher percentage of signals during the run-in interval. Especially Brown's and Trigg's method suffered from this draw back. Hence, they were excluded from the simulation research. The above mentioned phenomenon, under Trigg's method, is illustrated next. Section 4.1 described how HW forecast errors were generated. The first level and trend estimates are strongly influenced by the noise in the series, which causes the first few forecast errors to be rather large. In the simulation research, Trigg's tracking signal generally rose (fell) rapidly to about 0.8 (-0.8) in the run-in period after which it declined (inclined) considerably to a fairly constant level. Figures 2 and 3 show a typical simulation run.

In most simulation runs Trigg's method yielded already a signal during the run-in interval. When no signal was given in the run-in interval, it would take a long time to get a false alarm. Hence, a false alarm rate much smaller than 0.01 signals per period, was obtained.

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Authors' biographies

Hendrikx, A.L.P.M. is a member of the Forecasting and Planning Support staff of the Centre for Quantitative Methods, Nederlandse Philips Bedrijven B.V., Eindhoven, The Netherlands. He obtained his M.Sc. in Econometrics at the University of Tilburg in 1986.

Heuts, R.M.J., obtained his Ph. D. in Econometrics at Tilburg University where he is currently assistant professor of management science. His research interests include time series analysis, portfolio analysis and production-inventory modelling. He has published in the Australian Journal of Statistics, Zeitschrift für Operations Research, Computational Statistics Quarterly, among others.

Hoving, L.G. is responsible for the coordination of the activities in the field of Forecasting and Planning Support of the Centre for Quantitative Methods, Nederlandse Philips Bedrijven B.V., Eindhoven, The Netherlands. He joined the Philips concern in 1973 after obtaining his M.Sc in Mathematical Statistics at the State University of Groningen in 1972.
Within Philips all his activities were in the field of business applications of statistics, including forecasting.

FIGURE 1
PERFORMANCE OF SEVERAL MONITORING METHODS FOR A STEP DISTURBANCE
IN NID FORECAST ERRORS

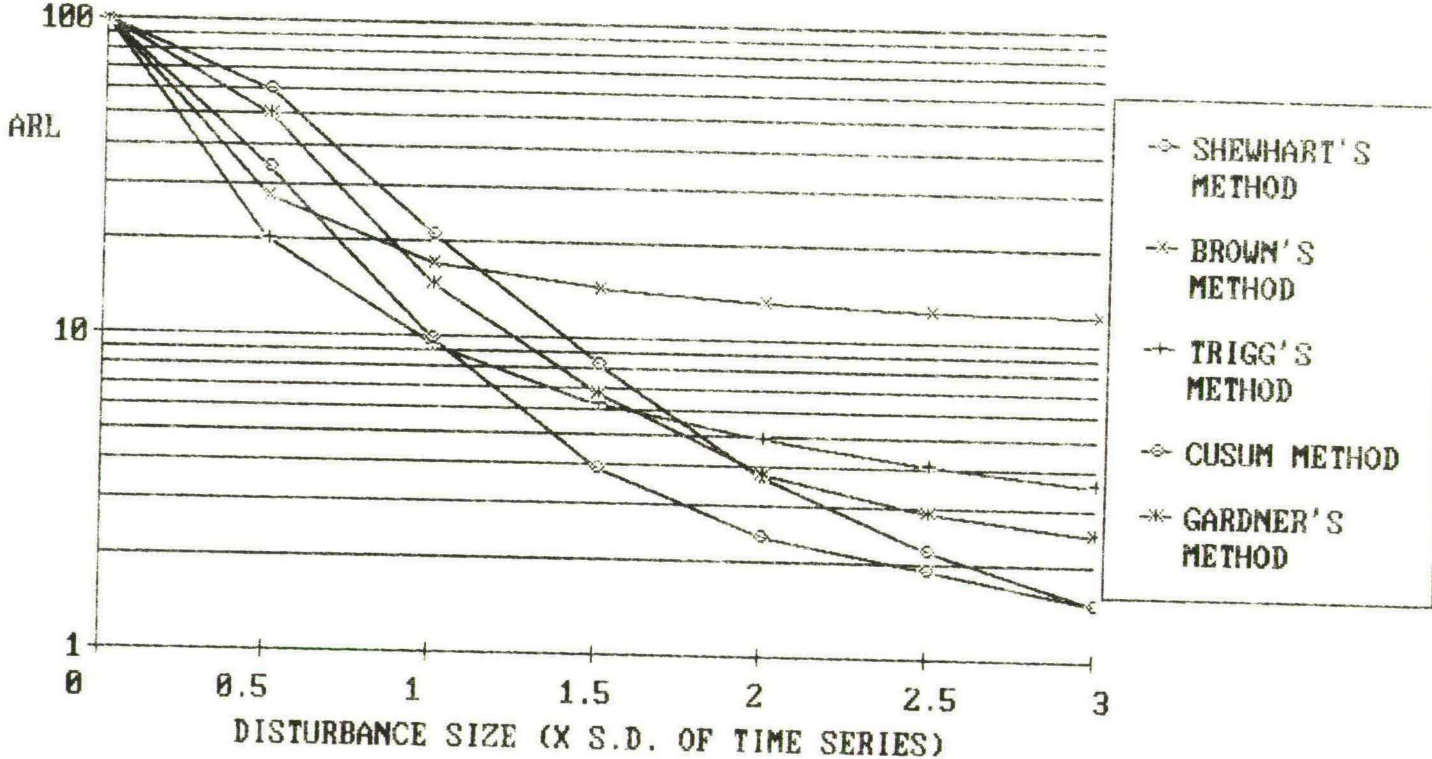


FIGURE 2
HOLT-WINTERS' FORECAST ERRORS

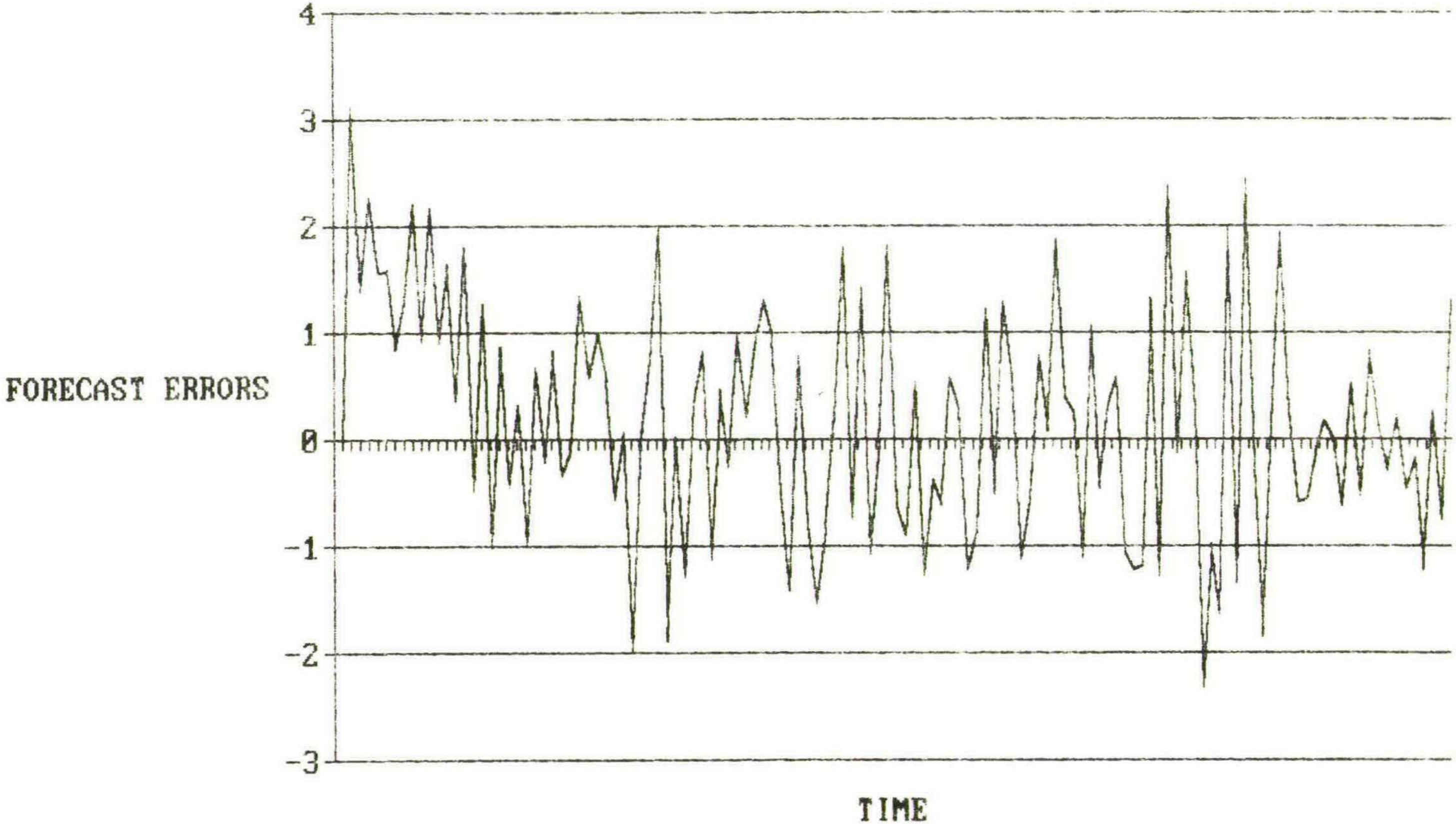


FIGURE 3
TRIGGS' TRACKING SIGNAL

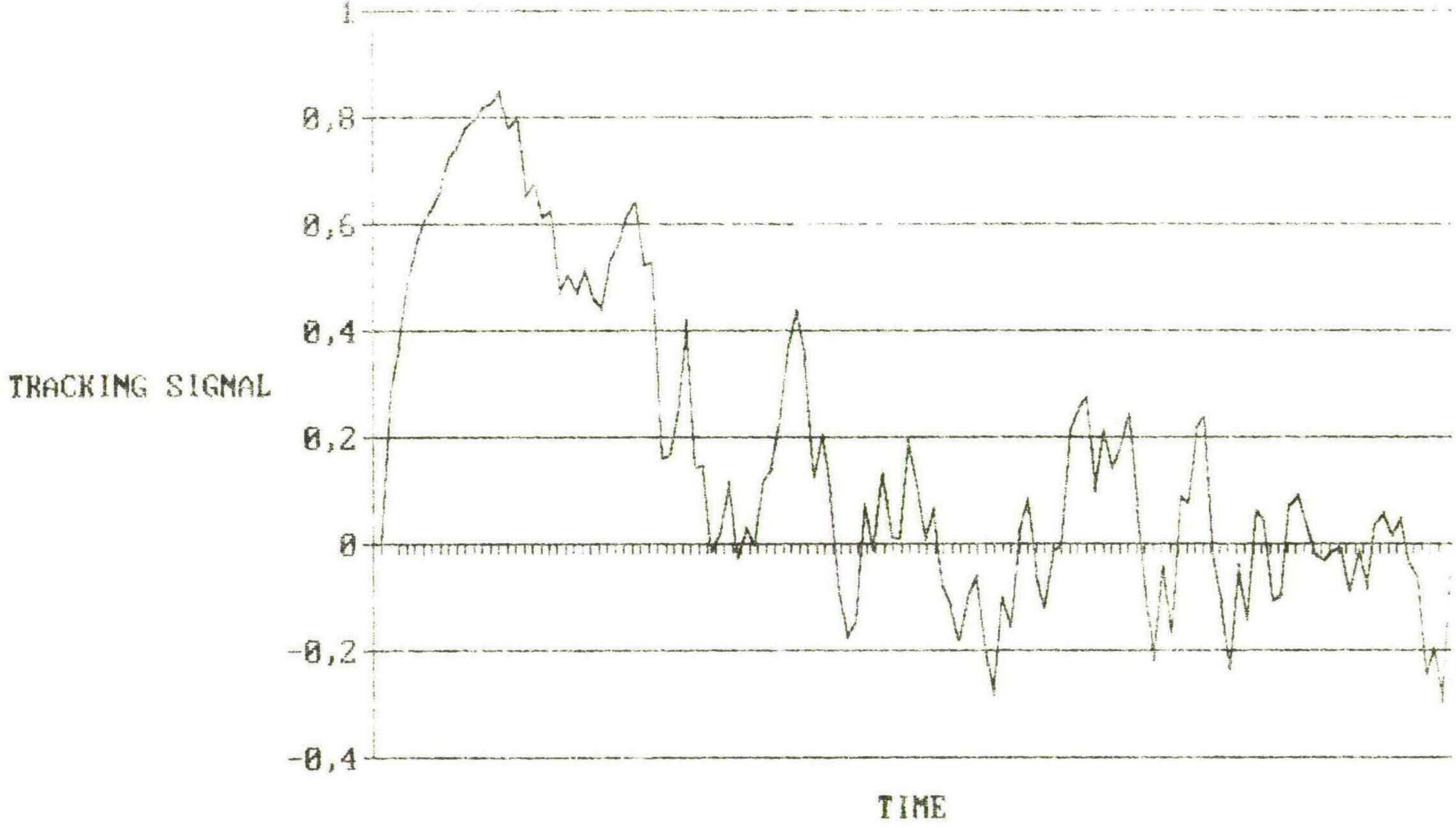


FIGURE 4
PERFORMANCE OF THE CUSUM METHOD FOR SEVERAL PROCESS DISTURBANCE TYPES
AND SES FORECAST ERRORS

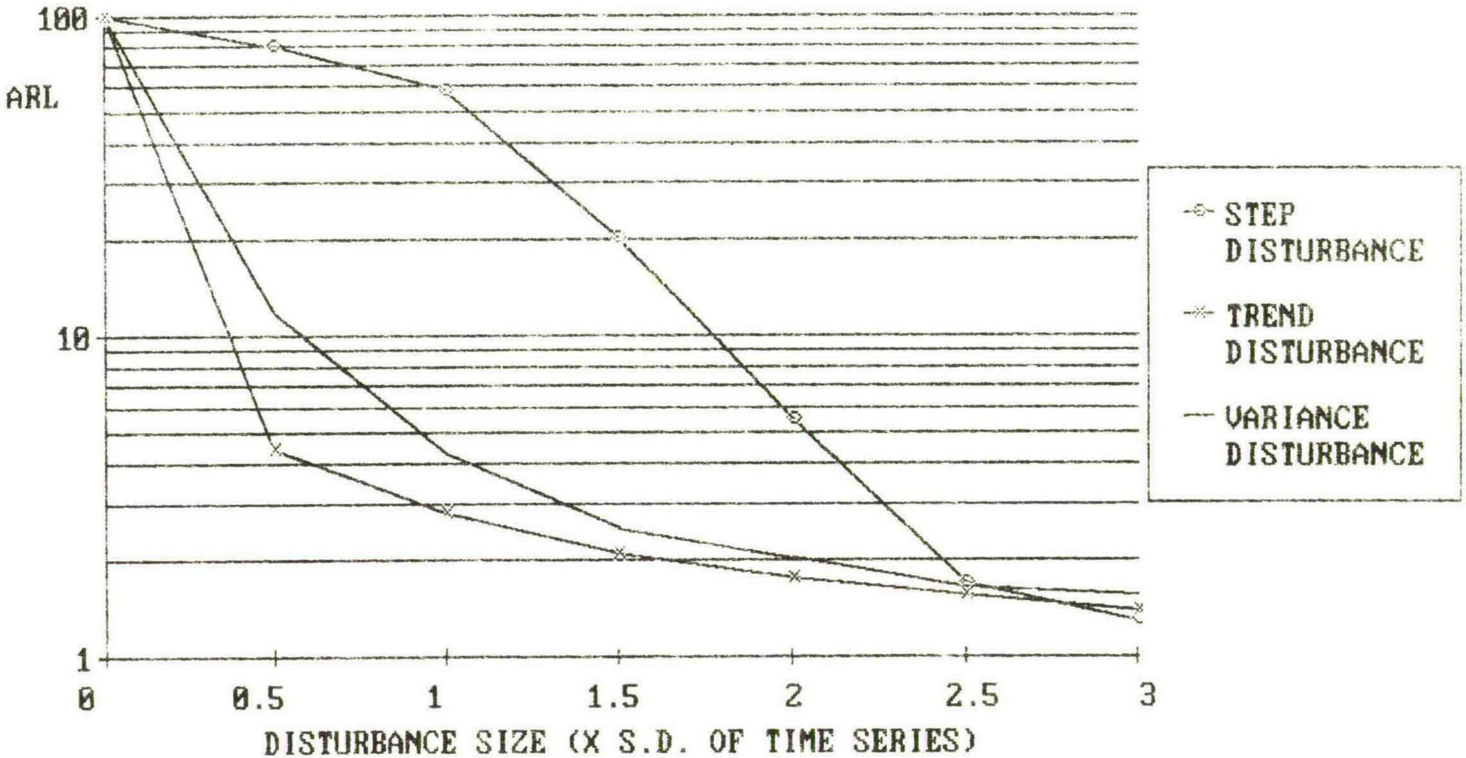
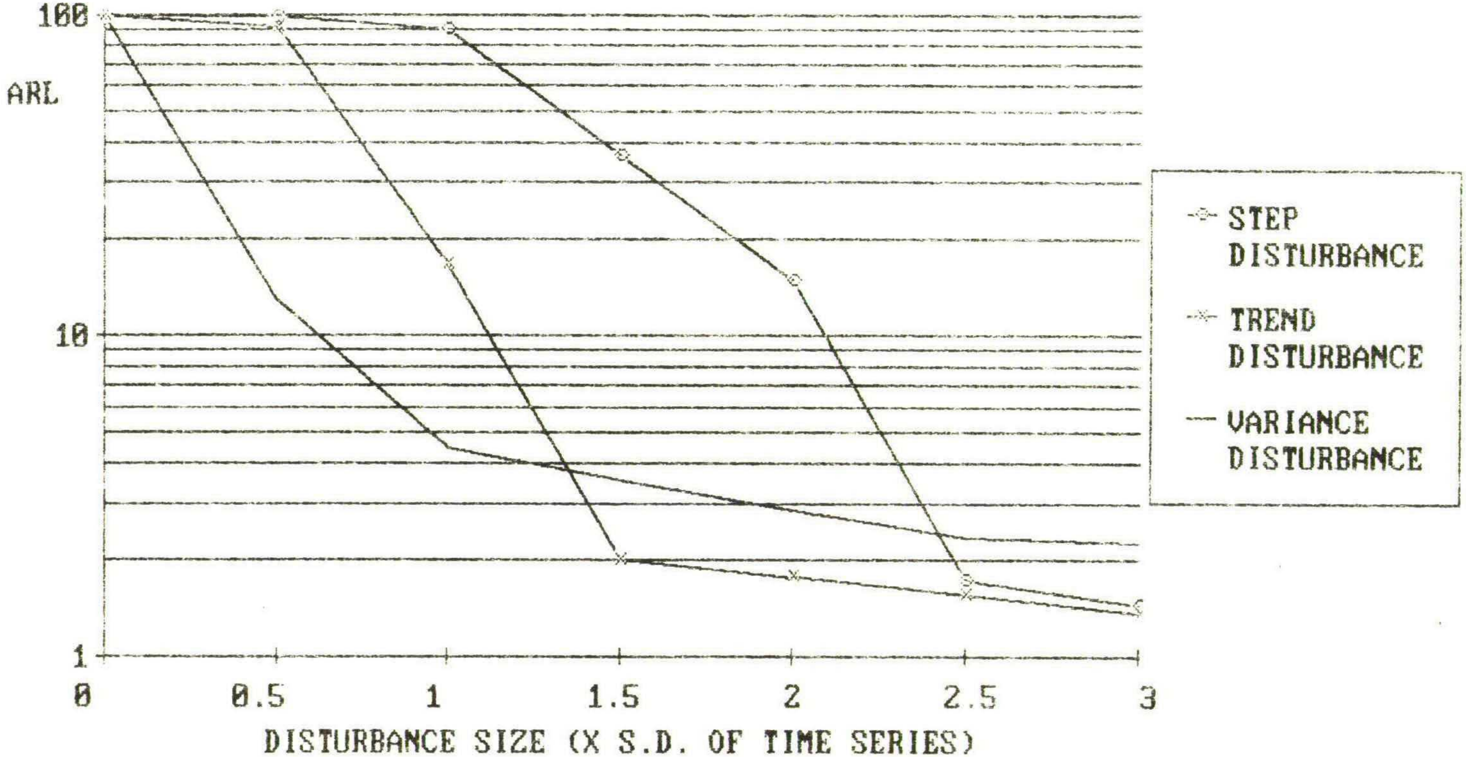


FIGURE 5
PERFORMANCE OF THE CUSUM METHOD FOR SEVERAL PROCESS DISTURBANCE TYPES
AND HW FORECAST ERRORS



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